Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets

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Abstract

We analyse, in the time and frequency domains, the relationships between three popular cryptocurrencies and a variety of other financial assets. We find evidence of the relative isolation of these assets from the financial and economic assets. Our results show that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Time variation in the linkages reflects external economic and financial shocks.

Keywords: Cryptocurrencies, bitcoin, litecoin, time varying, GARCH, spillovers

1. Introduction

The dramatic growth of the virtual currencies challenge politicians and policy makers around the globe. Virtual currencies not only resemble the role of money, but also create an alternative environment for businesses. Cryptocurrency markets have recently experienced increased speculative demand exceeding their role of digital money, placing them into the category of investment assets. For the period from

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October 2016 to October 2017 the market capitalisation of the Bitcoin increased from 10.1 to 79.7 billion, while the price jumped from 616 to 4800 US dollars. The remarkably high growth has been also evident for other cryptocurrencies, like Ripple and Litecoin, during this period. It is not surprising therefore, that investors attracted by the high growth of cryptocurrencies seek to achieve these abnormal returns.

However, due to the limited understanding of the nature of cryptocurrencies as investment assets, desirable returns may be not forthcoming. Investments involve a substantial level of risk due to the high volatility of cryptocurrencies (Katsiampa [2017]; Vandezande [2017]). While investors can choose to invest in various markets it is vital to understand the behaviour of return and volatility of the cryptocurrencies in relation to other important financial assets to explore the benefits of diversification. Additionally, tremendous growth of the cryptocurrencies is driven by anonymity of the internet (Bariviera et al. [2017]), making the prices prone to speculative bubbles (e.g.,Cheah and Fry [2015a]). The burst of the bubble may create a significant volatility shock that will spillover to other financial markets. The contagion effect will erase the benefits of portfolio diversification, and may violate the stability of the whole financial system (Yarovaya et al. [2016]). Therefore, it is crucial to identify the patterns of information transmission across cryptocurrencies markets and other asset classes.

Cryptocurrencies have become an increasingly important topic widely covered by the media, and discussed by government bodies, businesses and academic communities. Besides the numerous policy papers and reports (e.g. European Central Bank, 2012; European Banking Authority, 2014, Financial Action Task Force, 2015), there were significant attempts by financial scholars to analyse cryptocurrencies as investment assets. Recently, the focus of the research has expanded from the technical aspects and stylised facts of cryptocurrency markets (e.g. Dwyer, 2015; Bariviera et al., 2017) to a variety of issues, such as hedging and safe haven properties of cryptocurrencies (e.g. Bouri et al. [2017];Bouri et al. [2017]), return-volume relationships (e.g. M. et al. [2017]), speculation (e.g., Yermack, 2013; Glaser et al., 2014; Blau [2017]) and market efficiency (e.g., Urquhart [2016]; Bariviera [2017]; Nadarajah and Chu, 2017), to name but a few. The majority of these papers, however, focused solely on Bitcoin, omitting other cryptocurrencies. Furthermore, there is a lack of research on interconnectedness of the cryptocurrencies with other markets.

To fill this gap, in this paper we examine the return and volatility transmission across three cryptocurrencies, i.e. Bitcoin, Ripple and Litecoin, and gold, bond, equities and the global volatility index (VIX). To our best knowledge, this is the first study that addresses the issue of connectedness of these cryptocurrencies with other financial assets using return and volatility spillover analysis. This paper contributes to existing literature in three ways. First, we provide the novel empirical evidence on the patterns of return and volatility transmission using the Diebold and Yilmaz [2012] methodology. Particularly, we shed the light on the main channels and dynamics of information transmission across markets, highlighting who are the net-recipients and net-contributors of the return and volatility spillovers. Second, we employ Barunik and Krehlik [2015] methodology to estimate unconditional connectedness between markets in time-frequency domain. Our findings provide the evidence on connectedness between markets in short-, medium-, and long-run. Third, and as a robustness check we examine connectedness via a standard MVGARCH-DCC model.

All three show that cryptocurencies are relatively isolated from market shocks and are decoupled from popular financial assets. Alternatively, the performance of cryptocurrencies are strongly interlinked to one another.

Our paper is organized as follows. Section 2 provides a brief introduction to the area of cryptocurrencies. Section 3 presents our data and some preliminary statistics, Section 4 briefly presents the econometric framework and Section 4.3.1 discusses the findings. Section 5 concludes the paper.

2. Cryptocurrencies

The role of cryptocurrencies as an investment asset is under-researched. There is a lack of financial theories that can fully explain current behaviour of the cryptocurrencies as well as the future of this financial instrument. In this paper we briefly discuss the most recent debates in this topic area that form the theoretical background of our research.

The first group of papers that highlights the importance of the research on cryptocurrencies examined the risk associated with these markets. The impact of rapid growth of virtual currencies is still unknown and highly uncertain. Therefore, policy makers and regulatory bodies are particularly concerned about the recent tremendous growth of cryptocurrencies. In 2012, the European Central Bank (2012) concluded that cryptocurrencies do not jeopardise financial stability, due to their limited connection to the real economy, the low volumes traded and the lack of wide user acceptance.[2] However, the growth of cryptocurrency markets and their integration to the global economy must be monitored, since cryptocurrencies remain the potential source of financial instability. The risk assessment of the virtual currencies that has been conducted by European Banking Authority (2014) indicates the ab-

[2]Please see European Central Bank (October, 2012) Virtual Currency Scheme: https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf

sence of any specific regulatory protections in the EU that would protect users from financial losses in situation of the virtual trading platform or business crashes.[3] Financial Action Task Force (2014) highlights that since the Bitcoin protocol does not require identification and verification of participants, the anonymity of cryptocurrencies increases the risk of money laundering and terrorist financing using this payment instrument.[4] Among academics, there is a number of papers that considered the risk of cryptocurrencies from policy perspective. Vandezande [2017] analysed the anti-money laundering legislations of the virtual money providing insight to the nature of the cryptocurrencies as alternative money. Vandezande [2017] discussed the risk associated with cryptocurrencies for users of virtual currencies, investors and service providers. The cryptocurrencies have the highest risk among all types of virtual currencies, since investors are not fully informed about the risk due to the absence of sufficient protection mechanisms from regulatory bodies (Vandezande [2017]). The current absence of adequate regulations makes cryptocurrencies one of the key areas that requires an adequate response from policy makers (European Commission, 2016). Therefore, it is increasingly important to analyse the current behaviours of major cryptocurrencies in relation to other assets to equip policy makers and regulatory bodies on the role of the cryptocurrencies as an investment asset.

The second group of papers that motivates our research includes studies that considered price dynamics and speculation bubbles in the cryptocurrency markets. The literature is highly inconsistent. Cheah and Fry [2015b] claimed that cryptocurrencies are prone to substantial speculative bubbles, while the fundamental value of Bitcoin is zero. Cheah and Fry [2015b] analysed the daily closing prices for the Bitcoin Coindesk Index for the period from 18 July 2010 to 17 July 2014, and Bitcoin prices from 18 July 2010 to 31 December 2012. More recently, Blau [2017] argued that high volatility of the Bitcoin is not related to the high speculative activity in this period. The volatility of the cryptocurrencies has been also analysed by Katsiampa [2017], Fry and Cheah [2016], Pieters and Vivanco (2017), to name but a few. The ambiguity of the results exemplifies the debates about whether the cryptocurrencies is a speculative investment asset or a currency. To be considered as a currency (i.e. money), cryptocurrencies should serve as a medium of exchange, be used as a unit of account, and allow to store value; however, cryptocurrencies are barley managing to fulfil all those properties (Bariviera et al. [2017]). Crytocurrencies bear a strong

[3] European Banking Authority, Opinion on 'virtual currencies' http://www.eba.europa.eu/-/eba-warns-consumers-on-virtual-currencies

[4] Financial Action Task Force, 2014, 'Virtual Currencies: Key Definitions and Potential AML/CFT Risks'

resemblance to pre-modern financial instruments such as goldsmith notes and bills of exchange which operated as "near monies" during the Financial Revolution 1688-1756. (Roberds and Velde, 2014) Roberds, W. and Velde, F.R., 2014. Early public banks, Federal Reserve Bank of Atlanta Working Paper Series (No. 2014-9)

To be considered as a separate asset class, cryptocurrency markets should demonstrate a high level of integration, to respond to common shocks in a similar manner, and consequently, the return and volatility transmission across these markets should demonstrate similar patterns. Thus, we hypothesise that *cryptocurrency markets, i.e. Bitcoin, Ripple and Litecoin, are strongly interconnected, and demonstrate similar patterns of return and volatility transmission with other assets*. The acceptance of this hypothesis will confirm that cryptocurrencies can be considered as a separate class of investment assets.

The third group of papers that justify the importance of testing our research hypothesis is papers that assess the linkages of cryptocurrencies with other assets and markets. Despite extensive research on the economics of cryptocurrencies, there remains a relative dearth on their interlinkages to other assets. A number of papers have analysed the ability of cryptocurrencies, usually Bitcoin, to act as safe havens or hedges. Examples include [Dyhrberg, 2016b], [Dyhrberg, 2016a], [Bouri et al., 2017], [Bouri et al., 2017] and [Bouri et al., 2017]. Dyhrberg [2016a] analysed the hedge properties of Bitcoin using a selection of explanatory variables such as gold (cash and future), the dollar- euro and dollar-pound exchange rates and the FTSE 100 index. The results of the GARCH model showed that Bitcoin can be used in hedging against the dollar and the UK stock market, showing similar hedging capabilities to gold. Bouri et al. [2017] used a quantile regression approach to analyse the relationships between the Bitcoin and global uncertainty. The findings demonstrate that at the longer frequencies VIX have strong negative impact on Bitcoin returns, while at the shorter frequencies uncertainty does have positive and significant impacts only on high quantiles. This implies that Bitcoin can hedge against global uncertainty at short investment horizons and in the bull regime only. Another study by Bouri et al. [2017] investigated interrelationships between Bitcoin and the world equity indices, bonds, oil, gold, the general commodity index and the US dollar index using the bivariate DCC model by Engle (2002). The results show limited evidence of hedging and safe haven properties of the Bitcoin, however, Bitcoin still can be an effective diversifier.

Finally, there is a number of papers that analysed the information transmission mechanism across financial markets using various econometrics techniques. These studies are also motivated our research providing empirical evidence on methods and techniques that are found to be effective in analysis of the interconnectedness across different financial assets. For example, the return and volatility spillovers across equity markets have been analysed using the VAR methodology by Eun and Shim [1989], Huang et al. [2000], Climent and Meneu [2003], Singh et al. [2010], Diebold and Yilmaz [2009] ; ARCH model by Hamao et al. [1990]; an asymmetric BEKK model by Li and Giles [2015]; FIAPARCH by Dimitriou et al. [2013], to name but a few. Diebold and Yilmaz [2009] introduced the spillover index approach that become widely used in studies on market interconnectedness. Engle [2002] introduced the dynamic conditional correlation (DCC) estimator that also was employed by many studies due to the several advantages over multivariate GARCH models (e.g. Ahmad et al. [2013]). The interconnectedness between different asset classes has been analysed by Narayan et al. [2010], Antonakakis and Kizys [2015], Lau et al. [2017] using different combinations of the above-mentioned methods. However, just a few studies have focused on interconnectedness across cryptocurrencies and other markets (Bouri et al. [2017]).

Our aim here is threefold. First, to provide an analysis of the extent and time variation in the connectedness of these assets to other financial assets; second to link, where possible, changes in the degree of interconnectedness to market and economic events; third to examine the connectedness and interrelatedness of these assets over short and long horizons.

3. Data

Data are collected from a variety of sources. We collect data for the cryptocurrrencies from CryproCompare.com; data on the other assets are collected from Bloomeberg. We focus on larger cryptocurrency assets , those with a market value over $1b as of end July 2017. Further, to obtain as long a period as possible, we restrict our analysis to currencies with data back to 2013. Thus we examine Bitcoin, Ripple and Litecoin. To examine how these relate to other assets we select representative classes of same. We therefore collect the MSC GSCI Total Returns Index, to examine relationships with commodities ; the US$ Broad Exchange Rate, to examine relationships with the US Dollar and the FX market more generally; the SP500 Index and the COMEX closing gold price provide insight into relationships with equity and precious metal markets; VIX show any relationship with market volatility while the bond market is captured by the Markit ITTR110 index. In Figure 2 we see the evolution of these assets. Figure 1 shows a correlation matrix of the changes of these currencies and the other assets involved. Finally in Figure 3 we see that the volatility of the cryptocurrencies is significantly and manifestly higher than that of the other assets. Data for the cryptocurrencies from the website was collected for starting dates between early 2013 and early 2016, giving between 1400 and 400 observations. to obtain the longest series of data for the methods used we confine ourselves in the main to the analysis of three cryptocurrencies: Bitcoin, Ripple and Litecoin. Daily returns are defined as:

$$R(t) = ln(P_t) - ln(P_{t-1}) \tag{1}$$

where $ln(P_t)$ is the natural logarithm of the closing price at date t and $ln(P_{t-1})$ is the natural logarithm of the closing price at date $t-1$. We calculate volatility as the 5day standard deviation of variables.

4. Empirical Approach

4.1. Generalized variance decomposition

We employ the generalized variance decomposition methodology by Diebold and Yilmaz [2012] (hereafter DY) to measure the direction and intensity of spillovers across selected markets. The methodology allows us to obtain total, directional and net spillovers indexes for both levels and volatility. The Diebold and Yilmaz [2012] methodology has been previously employed by many papers analyzed directional connectedness between financial markets (e.g., Antonakakis and Vergos [2013] ;Batten et al. [2014]; Lucey et al. [2014] ; Balli et al. [2015],Yarovaya et al. [2016], Chau and Deesomsak [2014]. FernÃąndez-RodrÃŋguez et al. [2016]).

Using similar notations as Lau et al. [2017],the DY framework can be described as follows.

Consider a covariance stationary N-variable VAR (p), $Xt = \sum_{i=1}^{p} = \Psi_i X_{t-i} + \varepsilon_t$, where Ψ_i is a parameter matrix, and $\varepsilon \sim (0; \Sigma)$ is a vector of independently and identically distributed disturbances. The VAR model can be transformed into a moving average (MA) representation, $X_t = \sum_{i=o}^{\infty} A_i \varepsilon_{t-i}$, where A_i is and $N \times N$ is an identity matrix $A_i = \Psi_1 A_{i-1} + \Psi_2 A_{i-2} + ... \Psi_p A_{i-p}$ being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$. The DY framework relies on the N-variable VAR variance decompositions that allows for each variable X_i to be added to the shares of its H-step-ahead error forecasting variance, associated with shocks of relevance to variable X_j (where $\forall_i \neq j$ for each observation). This provides evidence on the information spillovers from one market to another. Besides detecting the cross variance shares, the DY framework defines own variance shares as the fraction of the H-step ahead error variance in predicting X_i due to shocks in X_i. Following Diebold and Yilmaz [2012] the methodological framework employed in this paper relies on KPPS H-step-ahead forecast errors, which are invariant to the ordering of the variables in comparison to the alternative identification schemes like that based on Cholesky factorization

(Diebold and Yilmaz [2009]) and can be defined for $H = [1, 2... + \infty)$, as:

$$\vartheta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Omega e_j)^2}{\sum_{h-0}^{H-1} (e_j' A_h \Omega A_h' e_i)} \tag{2}$$

where Ω is the variance matrix for the error vector ε; σ_{jj} is the standard deviation of the error term for the jth equation; e_i is the selection vector, with one as the ith element and zero otherwise. The sum of the elements in each row of the variance decomposition $\sum_{j=1}^{N} \vartheta_{ij}^{g}(H)$ is not equal to 1. The normalization of each entry of the variance decomposition matrix by the row sum can be defined as:

$$\tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N} \vartheta_{ij}^{g}(H)} \tag{3}$$

where $\sum_{j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H) = N$.

The total volatility contributions from KPPS variance decompositions are used to calculate the Total Spillover Index (TSI):

$$TSI(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \tag{4}$$

We also estimate Directional Spillover Indexes (DSI) to measure spillovers from market i to all markets j, as well as the reverse direction of transmission from all markets j to market i, using equations (5) and (6), respectively:

$$DSI_{j \leftarrow i}(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{5}$$

$$DSI_{i \leftarrow j}(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{6}$$

Finally, we calculate the Net Spillover Index (NSI) as the difference between total shocks transmitted from market i to all markets j and those transmitted to market i from all markets j:

$$NSI_{ij}(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} - \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 \tag{7}$$

The empirical results are presented in the form of spillover tables and spillover plots, as well as graphs, visualizing the intensity and the dynamics of spillovers across cryptocurrency markets and other selected markets. This approach also allows to understand who are net-contributors and net-recipients of spillovers. To our best knowledge, this framework has not been employed to cryptocurrencies data yet.

4.2. Time-frequency connectedness

In contrast to Diebold and Yilmaz [2012] that employs a VAR model, Barunik and Krehlik [2015] (hereafter BK) used spectral representations of variance decomposition method of Stiassny [1996] and Dew-becker and Giglio [2016] to estimate unconditional connectedness relations in time-frequency domain. This approach has been recently used by Lau et al. [2017] in an analysis of spillovers between the white precious metals and gold, oil and global equity. We also adopt Barunik and Krehlik [2015] approach to analyze the dynamics of spillovers across selected cryptocurrencies, bond, gold, FX, VIX, GSCI, and SP 500 market. This framework allows to investigate connectedness at short and long frequencies.

Using similar notations as Lau et al. [2017] and Barunik and Krehlik [2015] the methodology used to analyse the dynamic time-frequency connectedness can be described as follows. First, the frequency response function is used to decompose the generalized impulse response function. Consider the spectral behavior of series X_t as:

$$S_x(\omega) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ih\omega} = \Psi(e^{-ih\omega}) \sum \Psi(e^{ih\omega}) \tag{8}$$

where ω is the frequency, ∞ implies infinite horizon relations in the setting and $\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} \Psi_h e^{-ih\omega}$ (Barunik and Krehlik [2015]). The unconditional generalised forecast error variance decomposition (GFEVD) on a particular frequency ω is specified as:

$$(\Theta(\omega))_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \sum)_{i,j}^2}{\sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \sum \Psi(e^{ih\omega}))_{i,i}} \tag{9}$$

where 9 can be standardised as:

$$(\tilde{\Theta}(\omega))_{i,j} = \frac{(\Theta(\omega))_{i,j}}{\sum_{j=1}^{k} (\Theta(\omega))_{i,j}} \tag{10}$$

The accumulative connectedness table (i.e. specified over an informative frequency band) proposed by Barunik and Krehlik [2015] over an arbitrary frequency band $d = (a; b)$ can be expressed as:

$$(\tilde{\Theta}_d)_{i,j} = \int_a^b (\tilde{\Theta}(\omega))_{i,j} d\omega \tag{11}$$

Therefore the overall connectedness within the frequency band d can be defined as:

$$C^d = \frac{\sum_{i=1, i\neq j}^{k} (\tilde{\Theta}_d)_{i,j}}{\sum_{i,j} (\tilde{\Theta}_d)_{i,j}} = 1 - \frac{\sum_{i=1}^{k} (\tilde{\Theta}_d)_{i,i}}{\sum_{i,j} (\tilde{\Theta}_d)_{i,j}} \tag{12}$$

It is important to note that C^d close to unity implies strong connections within the spectral band ($d = (a; b)$) while the aggregate connectedness amongst the variables could be low. We are interested in measuring the contribution of one market ($i \neq j$) to another market i, which can be defined as *within from* connectedness on the spectral band d:

$$C^d_{i\leftarrow \cdot} = \sum_{j=1, i\neq j}^{k} (\tilde{\Theta}_d)_{i,j} \tag{13}$$

Similarly, we can measure the variance from market i to another market as the *contribution to* connectedness on the spectral band d:

$$C^d_{i\rightarrow \cdot} = \sum_{j=1, i\neq j}^{k} (\tilde{\Theta}_d)_{j,i} \tag{14}$$

We also quantify the difference between variance given and variance received from an asset by measuring net-spillovers. This *within net* connectedness is defined as:

$$C^d_{i,net} = C^d_{i\rightarrow \cdot} - C^d_{i\leftarrow \cdot} \tag{15}$$

If $C^d_{i,net}$ is positive, it indicates that the variable i is net-contributor of information in a stable VAR system, while if $C^d_{i,net}$ is negative it means that market i is net-recipient of the information. The pairwise connectedness *between* market i and j can be specified as:

$$C^d_{i,j} = (\tilde{\Theta}_d)_{j,i} - (\tilde{\Theta}_d)_{i,j} \tag{16}$$

The contribution of a particular frequency band d to the aggregate measure has to be weighted. Barunik and Krehlik [2015] show that the aggregate measure on the frequency band d is specified as:

$$\tilde{C}^d = C^d \cdot \Gamma(d) \tag{17}$$

Where the spectral weight $\Gamma(d) = \frac{\sum_{i,j=1}^{k}(\tilde{\Theta}_d)_{i,j}}{\sum_{i,j}(\Theta)_{i,j}} = \frac{\sum_{i,j=1}^{k}(\tilde{\Theta}_d)_{i,j}}{k}$ is the contribution of frequency band d to the whole VAR system and C^d is the total connectedness measure on the connectedness tables $(\tilde{\Theta}_d)$ corresponding to an arbitrary frequency of band d. The total connectedness measures C can be obtained by $S^g(H) = \sum_d \tilde{C}^d$ (Diebold and Yilmaz [2012]).

In this paper, we use the frequency domain analysis to estimate connectedness between markets in long- and short-run.

4.3. MVGARCH

As a robustness test we extend the above analysis to include a multivariate GARCH investigation of the volatility dynamics of our selected cryptocurrencies. GARCH models explicitly account for two unique features of the financial returns process: 1) time-varying volatility; and 2) volatility clustering. The motivation for applying an MGARCH framework is the potential discovery of return volatility relationships across market-related assets. It is clear from the earlier presented relationships between cryptocurrencies and other financial assets that the volatility of their associated returns are not constant over time. The analysis indicates that cryptocurrencies are highly sensitive to news events, especially those that have structural as opposed to market sentiment implications. Announcements related to the hacking or closure of exchanges, ICO regulations and "fork" decisions have the most profound impact.

GARCH models have the advantage of formulating an explicit dynamic model of volatility as opposed to ordinary least squares (OLS) models, which assume constant variance. Specifically, GARCH models allow researchers to analyse the size of the errors of the explanatory model and therefore to provide a volatility measure of the model's dependent variable (Engle2004). Generally univariate GARCH models do not account for systematic relationships in the volatilities of asset returns. Multivariate GARCH (MVGARCH) allow both the conditional mean and the conditional covariance to be dynamic. The general MVGARCH model is so flexible that not all the parameters can be estimated. Bollerslev (1990) proposed a constant conditional correlation (CCC) MVGARCH model in which the correlation matrix is time invariance. We utilize the work of Engle [2002] who introduced a dynamic conditional correlation (DCC) MVGARCH model in which the conditional quasi-correlations R_t follow a GARCH(1,1)-like process. To preserve parsimony, all the conditional quasi-correlations are restricted to follow the same dynamics, with the DCC MVGARCH model presenting itself as a more flexible model than earlier versions without introducing an inestimable number of parameters for a reasonable number of series.

Structural interdependencies in return-risk are captured by the dynamic behaviour of the conditional covariance matrix. Thus, the DCC MVGARCH framework allows for a more general analysis of the different periods of investigation analyses in the methodology. The model is specified by random walks in returns obtained by pre-filtering and a variance-covariance structure of prior-day return surprises. This formulation is now very standard.[5]

4.3.1. Structural events

To frame this analysis it is useful to highlight a series of structural events that take place over the time horizon of the data:

- November 2014: The US government closed the second version of Silk Road [6], a reincarnation of one of the world's largest black markets that had previously been shut down in November 2013. The FBI downloaded approximately 26,000 Bitcoins (worth an estimated US$3.6 million). Although only a relatively small amount compared to total market turnover, the FBI were then able to release sales volumes estimates of approximately US$1.2 billion on Silk Road, which proved that the marketplace had been driving the crytocurrencies evolution when considering that only US$1.5 billion Bitcoins were in existence. However, when these figures were released, it was expected that the value of Bitcoin would fall to zero. Instead, in the days following the closure of Silk Road, Bitcoin's value fell by 20% which led to a strengthening in market sentiment supporting its future viability. In the following months, US trading volume of Bitcoin doubled while Chinese trading volume trebled.

- July 2015: There was a large stress test of the Bitcoin network in the form of a flood attack, which is similar to a "denial of service attack" which provoked hundreds of thousands of transactions that filled up an entire block on their own. They were too large to be relayed by nodes, taking up to 20 seconds to complete. This extreme latency temporarily disrupted the network and subsequently caused market panic while reducing market sentiment. As a result

[5] We concentrate here on the evolution of the correlations. Details on the elements of the MV-GARCH estimates are available on request.

[6] A virtual black marketplace operating on the Deep Web which had launched in February 2011. It ran using Tor, which ensured anyone browsing could do so anonymously by bouncing messages back and forth on volunteer relays. According to the FBI, it ran off servers in several countries. It only accepted Bitcoin and used a "*tumbler*" to make tracking difficult, described as *"a complex, semi-random series of dummy transactions... making it nearly impossible to link your payment with any coins leaving the site"*.

of the attack, most mining pools updated their software to produce larger blocks so that the probability of such future successful attacks would be diminished.

- August 2015: On the 19th of August, while trading between \$250 and \$250, Bitcoin experienced a flash crash [7] which saw prices fall as low as \$179, representing a 29% collapse. Bitfinex, which was at the time one of the most liquid digital asset exchanges in the world stated that the flash crash was triggered when several leveraged positions were forcibly closed in quick succession and close proximity to one another. Due to a surprisingly small amount of liquidity on the book below \$225, it made it possible for the price to collapse to a far lower level before recovering. This flash crash was further fueled by margined speculation on the price of Bitcoin which amplified the movement of the cryptocurrency's price. The very nature of the event led to a reduction in sentiment surrounding Bitcoin and provoked substantial debate against the viability of cryptocurrencies at large should exchanges behave in such an immature fashion.

- Q2 and Q3 2016: In the second quarter of 2016 there were two large shocks that shaped the price of Bitcoin. The first was the result of the Brexit referendum on European membership. Bitcoin's price surged leading up to the Brexit vote, climbing approximately 47% between the 1st and 18th of June. However, in the days immediately before the referendum, the price of Bitcoin fell as low as \$551, but increased to almost \$675 in the immediate aftermath of the Brexit result. In the third quarter, there was a hack of the Bitfinex exchange on the 2nd of August which resulted in the loss of almost 120,000 Bitcoin. In the wake of the hack, the exchange temporarily stopped trading after the security breach was confirmed. Bitcoin prices declined almost 20% in response during the session, falling from approximately \$607 to \$408.

- Q1 2017: Ripple (XRP) was introduced on major exchanges such as Bitstamp along with the introduction of new trading pair arrangements XRP/EUR and XRP/USD. The introduction of a new enterprise wallet released allowing easier access by firms to Ripple. On 16 February 2017 Bitstamp brought in the first XRP/Bitcoin trading pair. Of all of the digital assets available on the market, XRP is unique in that it can be used as a bridge currency for real-time settlement, allowing for the efficient exchange of value across borders.

[7] A flash crash is best described as a very rapid, deep, and volatile fall in security prices occurring within an extremely short time period.

As we are concerned with the way in which the various cryptocurrencies interact with each other and with other financial assets, we first obtain Z-Scores of each of the dynamic relationship series. This not only has the effect of standardizing the results but shows more clearly when a significant divergence happens. In our analysis, we focus on Bitcoin, as the largest of the three cryptocurrencies

4.4. Time Domain Analysis

Application of a generalized variance decomposition framework reveals some interesting patterns. Table 1 displays the values of directional, pairwise and total spillover indexes (TSI). The results show that the TSI is higher for price *levels* (49.58%) than for *volatility* (38.04%), which pattern is also evident for the directional and pairwise indexes. The notable exceptions are for VIX, Lite and FX , which have higher values of direction spillovers (contribution to other markets) estimated for volatilities.

Insert Table 1 about here

The identified linkages between cryptocurrencies indicate that Bitcoin prices affect both Ripple (28.37%) and Lite (42.3%), but Ripple and Lite have limited influence on Bitcoin, the values of pairwise spillovers indexes being 7.11% and 5.47% respectively. Within the cryptocurrency market Bitcoin is the clear leader. However, for volatility spillovers the patterns are markedly different. Bitcoin volatility can explain only 6.39% of forecasting error variance of Ripple and 26.8% of Lite, which is lower than was found for levels. In contrast, the value of pairwise volatility spillovers from Lite to Bitcoin is 31.69%, and from Lite to Ripple is 15.95%. These results indicate that both Bitcoin and Ripple can be susceptible to volatility shocks transmitted from Lite. In summary, the price and volatility spillover tests demonstrate that Ripple and Lite are strongly interconnected.

Our results reveal that all selected cryptocurrencies are rather isolated from the other markets. The values for directional return and volatility from VIX, Bond, Gold, FX, SP500 and GSCI to cryptocurrency markets are very low. It would seem that over this period general financial market conditions are less important than structural conditions related to the design, operation and clearing of cryptocurrencies.

Among all cases, the highest values of pairwise indexes are found for price spillovers from FX to Bitcoin (4.18%), followed by Bond to Bitcoin (2.75%). Dyhrberg [2016b] and Dyhrberg [2016a] suggests safe haven properties for Bitcoin versus gold and FX markets, which would be consistent with this lack of linkage, as would the findings of Bouri et al. [2017], Bouri et al. [2017] and Bouri et al. [2017] Furthermore, the low linkages with other markets reinforce the findings in papers suggesting diversification opportunities for the investors.

We also investigated the recipients of spillovers from the cryptocurrency markets. For example, FX is a recipient of levels spillovers from both Bitcoin (15.25%) and Lite (9.64%) markets. Similarly, the value of pairwise spillovers from Bitcoin to GSCI (10.63%) is higher than from GSCI to Bitcoin (2.38%), which makes GSCI a net-recipient of the information transmitted from Bitcoin. Figure 4 plots the pairwise spillovers between Bitcoin and other assets for price levels during the period from 2013 to 2017.

Insert Figure 4 about here

An analysis of the dynamics of pairwise spillovers provides additional information on interconnectedness between the selected markets. The findings show that intensity of spillovers varies over time. Examining for example Bitcoin to Ripple suggests that the increased price for Ripple has been driven by the rapid growth of Bitcoin. The direction of this dependency was similar for all observation period. Alternatively, for Bitcoin-GSCI , we can see the instability of the relationships between markets. While spillover analysis reveals that GSCI is a recipient of spillovers from Bitcoin, the dynamics of spillovers indicates that the direction of spillovers changed in the Q2 of 2016 (Bitcoin's price surged leading up to the Brexit vote), and the beginning of 2017 (Ripple (XRP) entered the major exchanges such as Bitstamp). For Bitcoin VIX and SP500 , the spillover plot shows a high intensity of spillovers from Bitcoin to these markets in Q3 2015. This corresponds to the 29% collapse of Bitcoin prices on the 19th of August 2015, which caused a volatility shock transmitted to both VIX and SP500.

Figure 5 displays the dynamics of volatility spillovers from Bitcoin to other assets. The intensity of volatility spillovers is constantly changing during the estimation period. The direction of the identified relationships is inconsistent, and intensity of spillovers is highly erratic. We can suggest that the volatility spillovers are highly time dependent, relatively small in magnitude, and unstable

Insert Figure 5 about here

4.5. Frequency Domain Analysis

To further explore the interconnectedness between cryptocurrency markets and other assets at short and long frequencies we employ the Barunik and Krehlik [2015] methodology. Table 2 for levels and Table 3 for volatilities presents the decomposition of time-frequency dynamics of connectedness. We found that cryptocurrencies and other assets are typically not connected at short frequencies. At long frequencies, the results reveal similar patterns to those that have been discussed in previous section of this paper.

Insert Table 2 about here

According to the frequency domain analysis, there is little evidence of volatility spillovers between cryptocurrencies and other financial markets at short frequencies. However, the cryptocurrency markets influence each other at both long and sort frequencies. Table 3 presents the results for volatilities.

Insert Table 3 about here

We plot the pairwise spillovers between the Bitcoin and other assets to analyse the differences in connectedness in short- and long-run. Figures 6-11 show the dynamics of the pairwise spillovers at various frequencies. The results support the previous findings of this paper. However, there are several cases, where we can observe an increase in spillovers from Bitcoin to other markets at short frequencies. For example, Bitcoin-SP500 and Bitcoin-VIX levels during Q3 of 2015 (Bitcoin flash crash), Bitcoin-FX, Bitcoin-Gold and Bitcoin-GSCI levels during Q2 of 2016 (Brexit referendum).

Insert Figures 6-11 about here

We have introduced and analysed six major events that shaped public perceptions based on the validity of cryptocurrencies. The second Silk Road closure (November 2014), the Bitcoin flood attack of July 2015, the Bitfinex hack of August 2016 and the introduction of the XRP trading pairs produce relatively minor average spillovers between Bitcoin and the investigated financial products. However, there are consistent and elevated spillovers between Bitcoin and the same financial assets during both the build-up and aftermath of the Brexit referendum in mid-2016 and the Bitfinex hack of August 2016.

Focusing on specific financial products, there are consistent and strong spillovers between the investigated foreign exchange and bond series and Bitcoin when compared with our selected financial products. The VIX, gold and S&P series present frequent episodes of sharp interactions with Bitcoin during the investigated sample period, most notably in the period immediately before and after the Brexit referendum. The Silk Road closure, the Bitcoin Flash crash and Brexit referendum generated strong interactions between Bitcoin and all investigated financial products.

Investigating technological events, the July 2015 Flood attack generated moderate responses between Bitcoin and bonds and the Bitfinex hack generated responses between Bitcoin and GSCI, VIX and Ripple. The introduction of XRP trading pairs evoked strong correlations between Bitcoin and Ripple, but spillovers between Bitcoin and gold and the Bitcoin and foreign exchange products.

The DCC analysis also supports the increase in dynamic conditional correlation during the structural events discussed above. Figure 12 plots the DCC correlations for FX, SP500, Lite, Ripple, Bond, VIX and Gold with Bitcoin.

Insert Figure 12 about here

Figure 12 presents evidence of raw DCC correlation interactions between Ripple and Bitcoin at the time of the closure of Silk Road in November 2014 and very strong correlations at the point in time when XRP trading pairs are created in February 2017. The DCC correlations are also prevalent between Bitcoin and the foreign exchange and GSCI series at the time of the investigated Bitfinex flash crash in August 2015 and a very strong correlation between Bitcoin and the VIX at the time of the Brexit referendum in 2016.

4.6. DCC-MVGARCH Analysis

Structural interdependencies in return-risk are captured by the dynamic behaviour of the conditional covariance matrix. Thus, the DCC-MVGARCH framework allows for a more general analysis of the different periods of investigation analyses in the methodology. The model is specified by random walks in stock returns and a variance-covariance structure of prior-day return surprises:

$$R_{i,t} = c_i + \varepsilon_{i,t} \tag{18}$$

$$vech(\Sigma_t) = \Psi + A vech\left(\varepsilon_{i,t-1}, \varepsilon_{j,t-1}\right) + G vech\left(\Sigma_{t-1}\right) \tag{19}$$

Here *Vech(.)* is an operator that stacks the unique elements in the conditional covariance matrix Σ_{t-1} . The five-variate model contains the returns of a basket of cryptocurrencies (i=1), broad bond index (i=2), the returns of the SP500 (i=3), a broad currency index (i=4), and a commodity index (i=5). The included daily return distributions represent an equally-weighted portfolios of cryptocurrencies (representing the basket of Bitcoin, Ripple and Litecoin), as compared with the selected bond, equity, foreign exchange and commodities indices divided for the two sample periods. Sample (1) cover the full sample between 29 April 2013 and 7 February 2014, whereas sample (2) represents the full sample between 10 February 2014 and 30 April

2017. This sample division investigates the collapse of Mt. Gox which is observed by many cryptocurrency analysts as a defining moment in the life of Bitcoin and broad cryptocurrencies. Ψ is a vector containing N(N+1)/2=6 constant terms and A and G are diagonal matrices containing N(N+1)/2=6 parameters each. The A and G parameter matrices contain the ARCH and GARCH terms, and are specified as indefinite in order to provide the least restrictive form of the Diagonal-Vech model. For brevity, only the relationships relating to cryptocurrencies are presented, however, the relationships between all included variables are tested. The structural equations of the robustness testing model are listed in terms of the variances:

$$\sigma_{ii,t}^2 = \omega_{ii} + \alpha_{ii}\varepsilon_{ii,t-1}^2 + \gamma_{ii}\sigma_{ii,t-1}^2 \tag{20}$$

4.7. Mt Gox and After

The behavioral characteristics and subsequent relationships between cryptocurrencies and other types of financial market products has changed somewhat since 2013. We test the changing structural relationship while specifically investigating the collapse of Mt. Gox in February 2014 due to its broad impact across all traded cryptocurrencies, but in particular Bitcoin. Mt. Gox was a Bitcoin exchange based in Tokyo, Japan, which was launched in 2010. By 2014, it was handling over 70% of all Bitcoin transactions worldwide. However, in February 2014, Mt. Gox suspended trading, closed its website and exchange service and filed for bankruptcy protection from creditors. In April 2014 the company began liquidation proceedings[8].

Between February and March 2014, during the period during the closure of Mt. Gox, the value of Bitcoin declined by approximately 36%. It was during this period that the very perception of a viable future of the cryptocurrency was directly challenge, but it remained afloat. During this watershed moment, it is argued that Bitcoin and crytocurrencies at large had generated a somewhat tentative level of viability as an investment vehicle due to this evidence of resilience. We have therefore selected 10 February 2014 as the division of the two periods of investigation in the DCC-MVGARCH(1,1) analysis.

Insert Table 4 about here

[8]Mt. Gox had announced at this time that 850,000 Bitcoins belonging to customers and the company were missing and likely stolen, an amount valued at more than $450 million at that time. Evidence released in 2015 concluded that indeed most of these Bitcoins had been stolen straight from the exchanges wallet in a process that had begun in late 2011. By 2016, creditors of Mt. Gox had claimed that they had lost $2.4 trillion during the bankruptcy. The Japanese trustee overseeing the bankruptcy had found that only $91 million in assets had been tracked down to distribute to claimants.

Table 4 contains sample statistics for daily returns over the two selected sample periods, that before the collapse of Mt. Gox, and the period thereafter. Included are the means, standard deviations, measures of skewness and kurtosis and the Jarque-Bera statistics and Ljung-Box Q-statistic. Jarque-Bera test the null hypotheses that the daily returns are Gaussian distributed and serially uncorrelated. The kurtosis estimates indicate all of the return distributions are fat-tailed, more so in the period after the collapse of Mt. Gox for the market for cryptocurrencies.

Insert Table 5 about here

Table 5 reports the parameter estimates for the structural equations obtained for time period (1) and (2). The return volatilities from shocks in own-returns and cross-returns are reflected by the ARCH-GARCH parameters $(\alpha_{ii}, \gamma_{ii})$ and $(\alpha_{ij}, \gamma_{ij})$. And the corresponding parameter sums $(\alpha_{ii} + \gamma_{ii})$ and $(\alpha_{ij} + \gamma_{ij})$ measure the persistence of volatility between the two periods. Both measures must be less than one for systematic volatility to stabilise. This condition is satisfied throughout the estimated models $\delta(\alpha_{ii} + \gamma_{ii}) < 1$ and $\delta(\alpha_{ij} + \gamma_{ij}) < 1$. Furthermore, the measures of volatility persistence are found to change substantially between the selected non-cryptocurrency financial instruments, but cryptocurrencies themselves experience only a very marginal decline in cross-instrument persistence.

This evidence supports the view that there exists very little change in the persistence of volatility from shocks in cross-returns between the two periods, further indicating a continued decoupling between the selected portfolio of cryptocurrencies and the other investigated financial instruments as displayed through the substantially different results in other cross-return persistence of volatility.

Although crytocurrencies such as Bitcoin survived significantly negative episodes such as the collapse of the Mt. Gox exchange, they remain largely decoupled from the broad forms of major financial instruments. There has been an increase in the persistence of volatility from shocks in its own returns between the two investigated periods, however, there is little evidence of a change in the persistence of volatility from shocks in cross-returns between the same two periods.

5. Conclusion and Suggestions for further work

This paper explores the role of cryptocurrency markets in the integrated financial system. Application of spillover analysis revealed results important for financial traders, private investors, and policy makers.

First, we found that cryptocurrency markets are relatively isolated from market-driven external shocks. Our findings suggest that cryptocurrencies can be effective portfolio diversifier, and can offer safe haven properties for investor. The spillover tests based on a generalised VAR framework revealed that there is a very limited connectedness between cryptocurrency markets and other financial markets, e.g. gold, bond FX, SP 500, VIX and GSCI. The analysis of spillovers in time-frequency domain, demonstrated a lack of linkages across markets at short frequencies. Which indicate that for investors with short investment horizons can invest in cryptocurrency markets to increase the returns and decrease the risk of portfolio investments.

Second, the major cryptocurrencies Bitcoin, Ripple and Lite are interconnected. We found the Bitcoin price can affect the levels of Ripple and Lite. According to the identified dynamics of pairwise spillover, the influential power of Bitcoin is particularly evident for periods of rapid price increases in Bitcoin. Our results revealed the presence of positive contagion effect across cryptocurrency markets. This phenomenon can be explained by the global increase in demand on Bitcoin and other cryptocurrencies. The fact that cryptocurrency markets are decoupled from other popular financial assets, but interconnected with each other, can potentially indicate that the increase in cryptocurrency prices can be mainly due to the high speculative activity on these markets. However, we leave this issue for further research.

Third, the cryptocurrencies are highly sensitive to structural changes within their markets in the forms of changes to regulation, the operational effectiveness or presence/absence of an exchange and technological failures brought about by application design or malicious computer hacking. This is supported from the z-score results. While this once again underscores the usefulness of theses cryptocurrencies as part of an investment portfolio due to their separation from market fundamentals, it highlights their interconnectivity and their potential for volatility and limited liquidity during a period of cryptocurrency turmoil.

Our research has indicated there is a role for cryptocurrencies in an investor portfolio but that their structure and behaviour also indicate the cryptocurrency market contains its own idiosyncratic risks that are difficult to hedge against. Our results also support the position that cryptocurrency markets is a new investment asset class, since they are interconnected with each other and have similar patterns of connectedness with other asset classes. Further research is needed to observe the behaviour of cyrptocurrencies with respect to monetary policy and regulatory arbitrage.

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Table 1: Diebold Yilmaz Spillovers

Levels										
	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From
Bitcoin	76.56	7.11	5.47	0.37	2.75	0.56	4.18	0.61	2.38	2.6
Ripple	28.37	60.97	5.19	1.38	1.59	0.2	0.51	1.48	0.32	4.34
Lite	42.3	19.62	31.32	0.48	0.42	4	1.17	0.51	0.18	7.63
VIX	1.17	0.77	0.12	44.71	6.36	5.77	2.21	30	8.87	6.14
Bond	0.61	2.58	4.02	3.58	57.21	5.85	5.64	4.18	16.32	4.75
Gold	4.48	0.7	1.58	2.61	24.9	48.64	7.36	8.98	0.75	5.71
FX	15.25	0.85	9.64	2.43	4.87	3.87	38.23	19.8	5.07	6.86
SP500	2.1	1.09	3.3	20.9	11.9	4.11	1.68	41.25	13.67	6.53
GSCI	10.63	0.71	4.63	2.02	1.09	15.55	0.14	10.33	54.89	5.01
To	11.66	3.71	3.77	3.75	5.99	4.44	2.54	8.43	5.28	49.58
Volatility										
	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From
Bitcoin	61.64	3.52	31.69	0.72	0.16	0.43	0.35	0.28	1.22	4.26
Ripple	6.39	75.25	15.95	0.14	0.15	0.16	0.76	0.12	1.08	2.75
Lite	26.8	5.99	65.35	0.47	0.34	0.1	0.26	0.28	0.41	3.85
VIX	0.35	0.75	0.39	54.02	4.73	1.39	5.65	28.73	3.99	5.11
Bond	0.42	0.12	0.51	7.31	58.15	6.2	12.95	7.64	6.7	4.65
Gold	1.55	0.27	0.39	3.18	7.85	70.68	6.23	4.44	5.41	3.26
FX	0.35	1.11	0.52	6.48	10.52	3.48	61.35	7.06	9.13	4.29
SP500	0.77	1.19	0.25	30.87	5.97	2.49	5.1	46.87	6.48	5.9
GSCI	0.47	2.05	1.45	7.26	4.39	3.79	5.53	10.71	64.34	3.96
To	4.12	1.67	5.68	6.27	3.79	2	4.09	6.59	3.82	38.04

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Diebold and Yilmaz [2012] methodology.

Table 2: Frequency Domain Spillover Table for Levels

Short	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From A	From W
Bitcoin	0.28	0.22	0.27	0	0.02	0	0.02	0	0.02	0.06	3.1
Ripple	0.01	0.74	0.03	0	0	0	0	0	0.01	0.01	0.34
Lite	0.11	0.1	0.96	0	0	0	0.01	0	0.01	0.02	1.27
VIX	0.02	0.01	0	4.15	0.55	0.18	0.09	3.03	0.16	0.45	22.84
Bond	0.01	0.01	0.02	0.06	0.47	0.19	0.03	0.11	0	0.05	2.54
Gold	0.02	0	0	0	0.04	0.66	0.05	0	0.04	0.02	0.87
FX	0.08	0	0.05	0.01	0.1	0.08	1	0.07	0	0.04	2.21
SP500	0.02	0.02	0.02	0.95	0.49	0.13	0.01	1.09	0.03	0.18	9.42
GSCI	0.07	0.01	0.02	0.09	0.04	0.02	0.01	0.27	0.23	0.06	3.03
To Abs	0.04	0.04	0.04	0.12	0.14	0.07	0.02	0.39	0.03	0.89	
To Wth	1.88	2.09	2.28	6.33	7.14	3.42	1.22	19.79	1.47		45.62
Long	**Bitcoin**	**Ripple**	**Lite**	**VIX**	**Bond**	**Gold**	**FX**	**SP500**	**GSCI**	**From A**	**From W**
Bitcoin	76.27	6.89	5.2	0.37	2.73	0.56	4.17	0.61	2.37	2.54	2.59
Ripple	28.36	60.23	5.16	1.37	1.58	0.19	0.51	1.48	0.31	4.33	4.42
Lite	42.19	19.52	30.37	0.48	0.42	4	1.16	0.51	0.17	7.61	7.76
VIX	1.16	0.77	0.12	40.56	5.81	5.59	2.12	26.97	8.71	5.7	5.81
Bond	0.6	2.56	4	3.51	56.75	5.66	5.61	4.07	16.31	4.7	4.8
Gold	4.46	0.7	1.58	2.61	24.85	47.97	7.31	8.98	0.71	5.69	5.8
FX	15.17	0.84	9.59	2.42	4.77	3.79	37.22	19.73	5.07	6.82	6.96
SP500	2.07	1.08	3.28	19.95	11.41	3.98	1.67	40.16	13.64	6.34	6.47
GSCI	10.57	0.7	4.61	1.92	1.05	15.54	0.13	10.05	54.66	4.95	5.05
To Abs	11.62	3.67	3.73	3.63	5.85	4.37	2.52	8.05	5.26	48.69	
To Wth	11.85	3.75	3.8	3.7	5.96	4.46	2.57	8.21	5.36		49.66

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Barunik and Krehlik [2015] methodology. To Abs and To Wth refer to absolute and within the estimated system. Long refers to horizons of greater than 4 days, while short refers to horizons of up to 4 days.

Table 3: Frequency Domain Spillover Table for Volatilities

Short	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From A	From W
Bitcoin	7.87	0.29	3.09	0.1	0.05	0.06	0.05	0.06	0.05	0.42	2.11
Ripple	0.36	10.19	0.53	0.02	0.02	0.03	0.01	0	0.02	0.11	0.56
Lite	3.48	0.53	9.83	0.1	0.13	0.06	0.07	0.07	0	0.49	2.5
VIX	0.09	0.01	0.07	10.85	1.23	0.5	1.1	6.4	0.81	1.13	5.75
Bond	0.07	0.02	0.19	1.79	18.7	2.59	3.59	2.4	1.09	1.3	6.61
Gold	0.07	0.01	0.04	1.08	2.98	20.82	2.43	1.69	1.43	1.08	5.47
FX	0.07	0.01	0.09	1.54	3.25	1.54	15.1	1.68	0.98	1.02	5.15
SP500	0.04	0.01	0.03	4.62	1.14	0.59	0.93	8.35	0.8	0.91	4.6
GSCI	0.05	0.03	0.02	0.9	0.9	1	0.85	1.15	12.81	0.54	2.76
To Abs	0.47	0.1	0.45	1.13	1.08	0.71	1	1.49	0.58	7.01	
To Wth	2.39	0.51	2.29	5.71	5.47	3.58	5.09	7.57	2.92		35.51
Long	**Bitcoin**	**Ripple**	**Lite**	**VIX**	**Bond**	**Gold**	**FX**	**SP500**	**GSCI**	**From A**	**From W**
Bitcoin	53.77	3.23	28.6	0.62	0.1	0.37	0.3	0.22	1.16	3.85	4.79
Ripple	6.02	65.06	15.42	0.12	0.13	0.13	0.75	0.12	1.06	2.64	3.29
Lite	23.32	5.46	55.52	0.37	0.21	0.04	0.19	0.21	0.41	3.36	4.18
VIX	0.26	0.74	0.32	43.17	3.5	0.89	4.55	22.33	3.19	3.97	4.95
Bond	0.35	0.1	0.32	5.53	39.45	3.61	9.35	5.24	5.61	3.35	4.17
Gold	1.49	0.26	0.35	2.1	4.88	49.86	3.8	2.76	3.98	2.18	2.71
FX	0.29	1.11	0.43	4.94	7.27	1.94	46.25	5.38	8.15	3.28	4.08
SP500	0.73	1.18	0.22	26.25	4.83	1.9	4.17	38.51	5.68	5	6.22
GSCI	0.42	2.03	1.43	6.36	3.49	2.79	4.68	9.56	51.53	3.42	4.26
To Abs	3.65	1.57	5.23	5.14	2.71	1.3	3.09	5.09	3.25	31.03	
To Wth	4.55	1.95	6.52	6.41	3.38	1.62	3.85	6.34	4.05		38.66

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Barunik and Krehlik [2015] methodology. To Abs and To Wth refer to absolute and within the estimated system. Long refers to horizons of greater than 4 days, while short refers to horizons of up to 4 days.

Table 4: Sample Statistics for return series

Investment Product	Sample Period	Mean	Std. dev.	Skewness	Kurtosis	JB-stat.	Ljung-Box (12)
Cryptocurrencies	1. 4/13 to 2/14	0.0045	0.0761	0.6826	7.7196	54.86	0.4277
	2. 2/14 to 4/17	0.0021	0.0405	0.0881	10.0477	78.36	0.0003
Bonds	1. 4/13 to 2/14	0.0000	0.0014	-0.6180	4.7942	41.59	0.7786
	2. 2/14 to 4/17	0.0000	0.0012	-0.0922	2.4278	59.04	0.1752
Commodities	1. 4/13 to 2/14	0.0004	0.0060	-0.4750	2.7267	26.28	0.9439
	2. 2/14 to 4/17	0.0002	0.0067	-0.3710	5.1969	42.73	0.3551
Foreign Exch.	1. 4/13 to 2/14	0.0002	0.0035	0.2972	2.2724	18.97	0.4246
	2. 2/14 to 4/17	-0.0002	0.0048	0.1760	4.7241	46.25	0.2309
Equities	1. 4/13 to 2/14	-0.0005	0.0107	-0.4422	3.2690	28.53	0.9153
	2. 2/14 to 4/17	0.0000	0.0075	0.3226	4.5419	46.32	0.2278

Note: The table reports sample statistics for daily return distributions of portfolios of cryptocurrencies, bonds, equities, foreign exchange and commodities calculated for the two sample periods, i.e. means, standard deviations, measures of skewness and kurtosis, and Jarque Bera (JB) and Ljung Box Q statistics. Sample (1) cover the full sample between 29 April 2013 and 7 February 2014. Sample (2) cover the full sample between 10 February 2014 and 30 April 2017. This sample division investigates the collapse of Mt. Gox which is observed by many cryptocurrency analysts as a defining moment in the life of Bitcoin and broad cryptocurrencies. The JB statistic is defined as JB=n/6(S^2+0.25K^2), where N,S denote sample size, skewness and kurtosis. As is typical, all of the sample return series exhibit abnormal skewness ($S \neq 0$) and excess kurtosis (K$>$ 3). The null hypothesis that the data are from a normal distribution is a joint hypothesis of the S=0 and K$<$3, and rejected accordingly. Under the null hypothesis that the series is white noise, the Q-statistic is distributed chi-square with k degrees of freedom, reflecting the number of autocorrelations. ***, **, and * indicate level of significance at 1%, 5%, and 10% respectively.

Table 5: MVGARCH(1,1) parameter estimates and diagnostic statistics

Product	**Sample Period**	c_i	ω_{ii}	α_{ii}	γ_{ii}	$\alpha_{ii}+\gamma_{ii}$	$\Delta(\alpha_{ii}+\gamma_{ii})$
Cryptocurrencies	1. 4/13 to 2/14	-0.0004	0.0002***	0.1094***	0.8501***	0.9595	
	2. 2/14 to 4/17	0.0026***	0.0001***	0.1534***	0.8331***	0.9865	+0.0270
Bonds	1. 4/13 to 2/14	0.0000	0.0000***	0.0507***	0.8591***	0.9098	
	2. 2/14 to 4/17	0.0001	0.0000	0.0116**	0.9617***	0.9733	+0.0635
Equities	1. 4/13 to 2/14	0.0004	0.0002***	0.0396	0.7708**	0.8104	
	2. 2/14 to 4/17	0.0004***	0.0000***	0.1211***	0.8204***	0.9415	+0.1311
Foreign Exch.	1. 4/13 to 2/14	0.0002	0.0000***	0.2078**	0.7343*	0.9421	
	2. 2/14 to 4/17	0.0002	0.0000***	0.0313***	0.9565***	0.9878	+0.0457
Commodities	1. 4/13 to 2/14	0.0005	0.0002***	0.0227*	0.8038***	0.8265	
	2. 2/14 to 4/17	0.0000	0.0001***	0.0170***	0.9084***	0.9254	+0.0989
Product	**Sample Period**		ω_{ii}	α_{ij}	γ_{ij}	$\alpha_{ij}+\gamma_{ij}$	$\Delta\alpha_{ij}+\gamma_{ij}$
Crypto/Bonds	1. 4/13 to 2/14		0.0004***	0.0906***	0.8396***	0.9302	
	2. 2/14 to 4/17		0.0001***	0.1766***	0.7325***	0.9091	-0.0211
Crypto/Equity	1. 4/13 to 2/14		0.0004***	0.0929***	0.8363***	0.9292	
	2. 2/14 to 4/17		0.0002***	0.1755***	0.7346***	0.9101	-0.0191
Crypto/Forex	1. 4/13 to 2/14		0.0003**	0.0923***	0.8377***	0.9300	
	2. 2/14 to 4/17		0.0001***	0.1624***	0.7595***	0.9219	-0.0081
Crypto/Comm	1. 4/13 to 2/14		0.0003***	0.0918***	0.8374***	0.9292	
	2. 2/14 to 4/17		0.0001***	0.1672***	0.7516***	0.9188	-0.0104
Bonds/Equity	1. 4/13 to 2/14		0.0000***	0.0523***	0.7197***	0.7720	
	2. 2/14 to 4/17		0.0000**	0.022*	0.5323***	0.5542	-0.2178
Bonds/Forex	1. 4/13 to 2/14		0.0000***	0.2343**	0.6676	0.9019	
	2. 2/14 to 4/17		0.0000***	0.0787**	0.7435**	0.8222	-0.0797
Bonds/Comm	1. 4/13 to 2/14		0.0000***	0.1563**	0.6573	0.8136	
	2. 2/14 to 4/17		0.0000***	0.1358***	0.5290	0.6648	-0.1488
Equity/Forex	1. 4/13 to 2/14		0.0000*	0.0352	0.7102***	0.7454	
	2. 2/14 to 4/17		0.0001**	0.1317***	0.8104***	0.9421	+0.1970
Equity/Comm	1. 4/13 to 2/14		0.0001*	0.0348	0.7179***	0.7527	
	2. 2/14 to 4/17		0.0000***	0.1195***	0.8287***	0.9482	+0.1955
Forex/Comm	1. 4/13 to 2/14		0.0000***	0.1738**	0.6517*	0.8255	
	2. 2/14 to 4/17		0.0000**	0.0360***	0.9535***	0.9895	+0.1640

Note: The table reports parameters for the MVGARCH(1,1) model fitted with sample data described in table (1). Own-return volatilities are characterized in the variance equations by the difference between the ARCH terms (α_{ii}) and GARCH terms (γ_{ii}). in sample (2) compared to sample (1). However, for each financial product, the sum of these terms ($\alpha_{ii}+\gamma_{ii}$) is different in sample (2) than that of sample (1) suggesting that the persistence of volatility from shocks in own-returns has changed. In this regard, crytocurrencies have not portrayed the same proportionate increase in the persistence of their own-returns when compared to the other four financial instrument portfolios in both periods. This is similar for the persistence of volatility from shocks as measured in the lower panel by ($\Delta\alpha_{ii}+\gamma_{ii}$). ***, **, and * indicate level of significance at 1%, 5%, and 10% respectively. This presents evidence of very little change in the persistence of volatility from shocks in cross-returns between the two periods.

Figure 1: Correlation Analysis

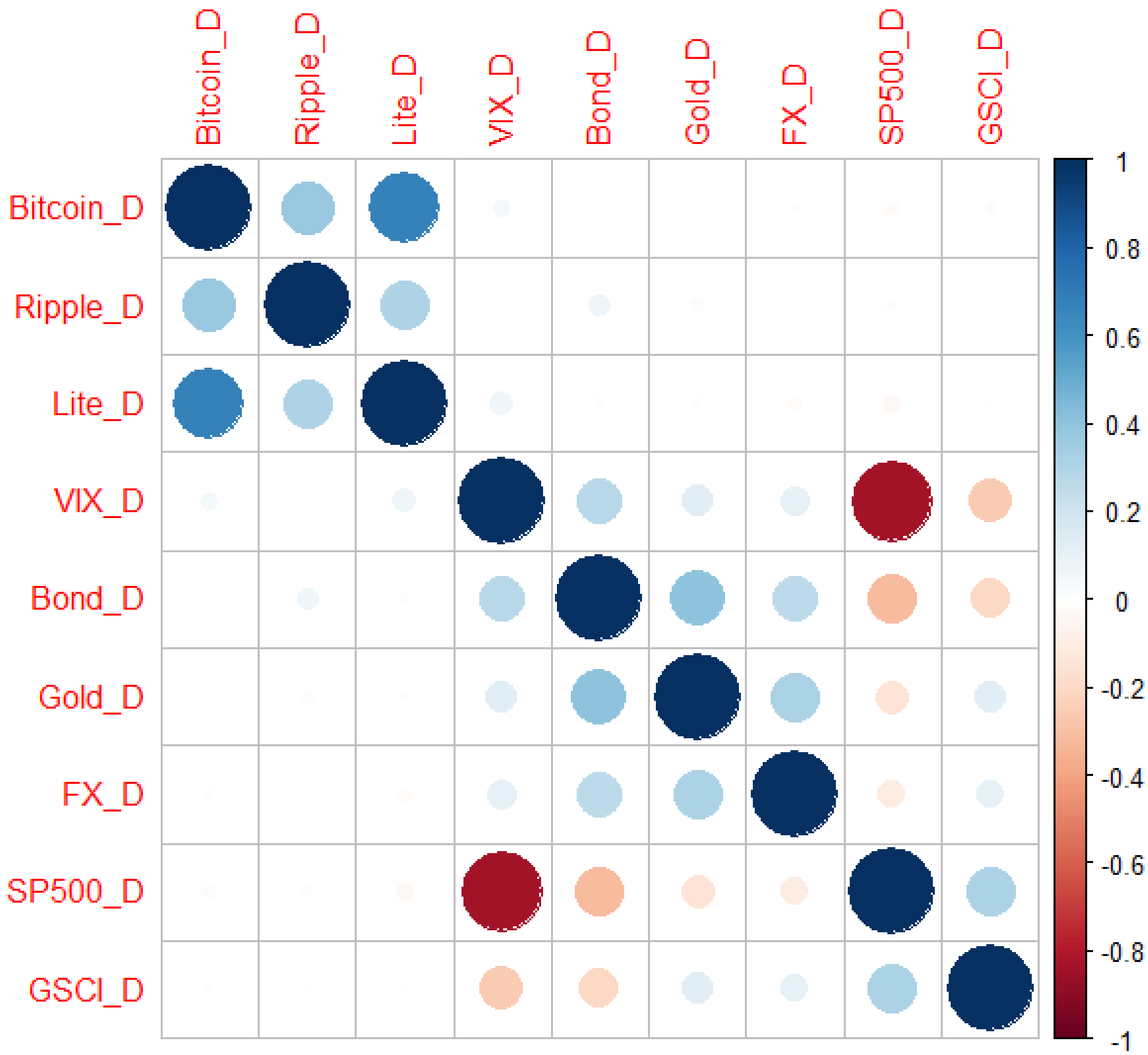

Figure 2: Evolution of selected Cryptocurrencies

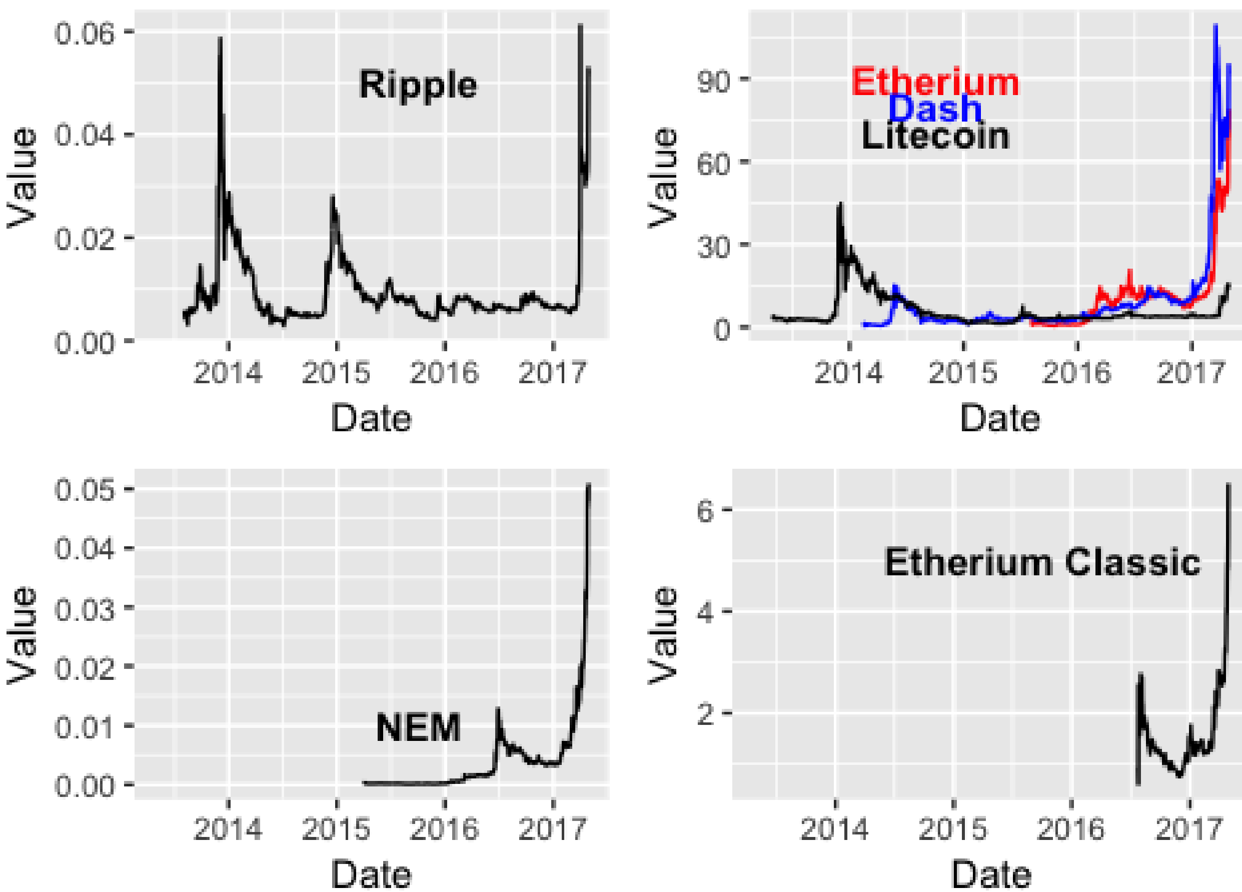

Figure 3: Box and whisker Analysis of volatilities

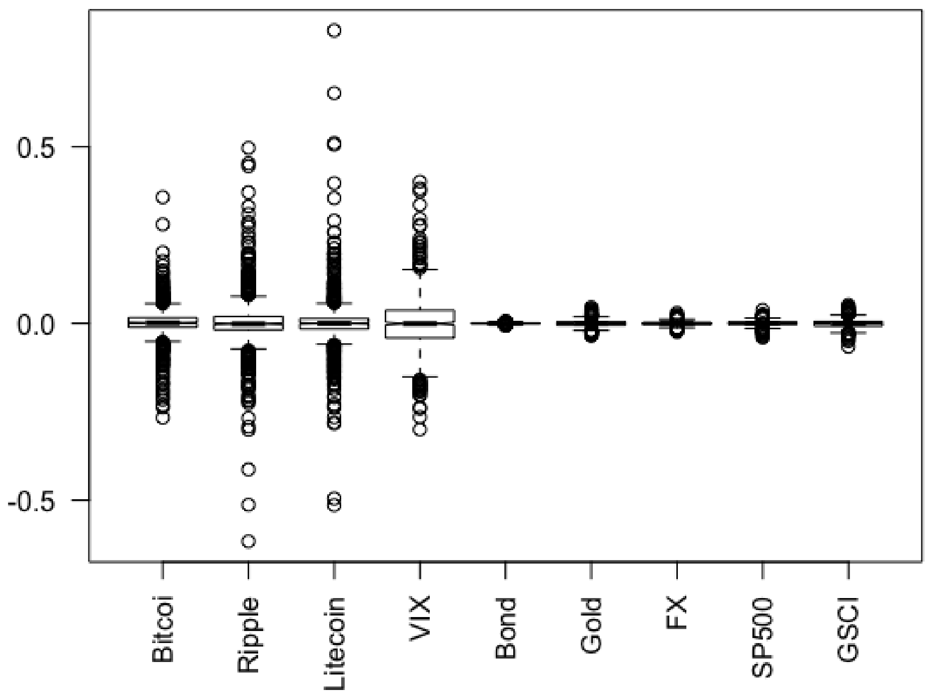

Figure 4: Diebold Yilmaz Pairwise Spillovers - Levels

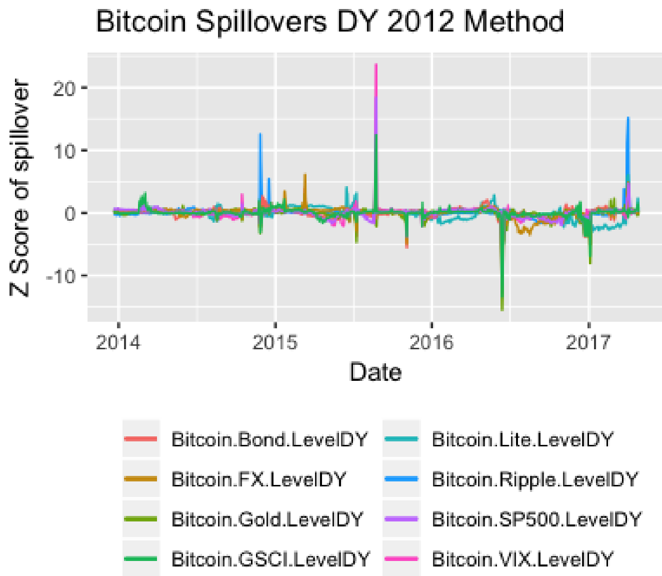

Figure 5: Diebold Yilmaz Pairwise Spillovers - Volatility

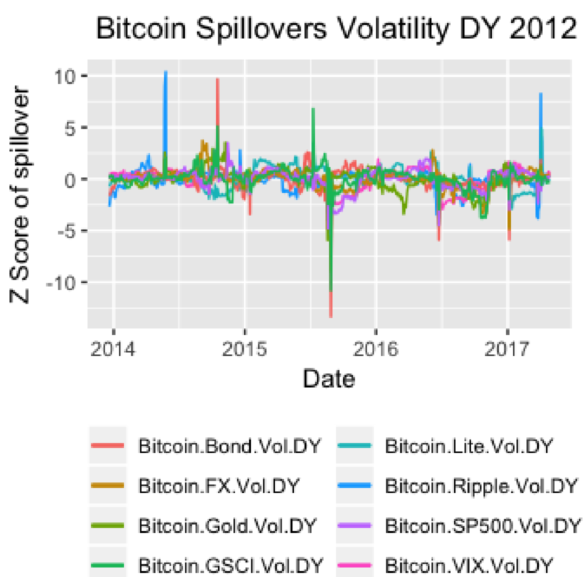

Figure 6: Bitcoin to Bonds

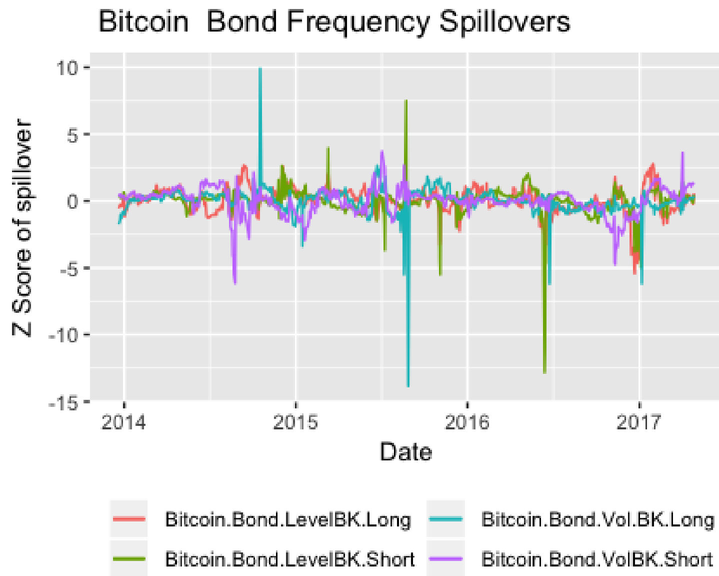

Figure 7: Bitcoin to Stocks

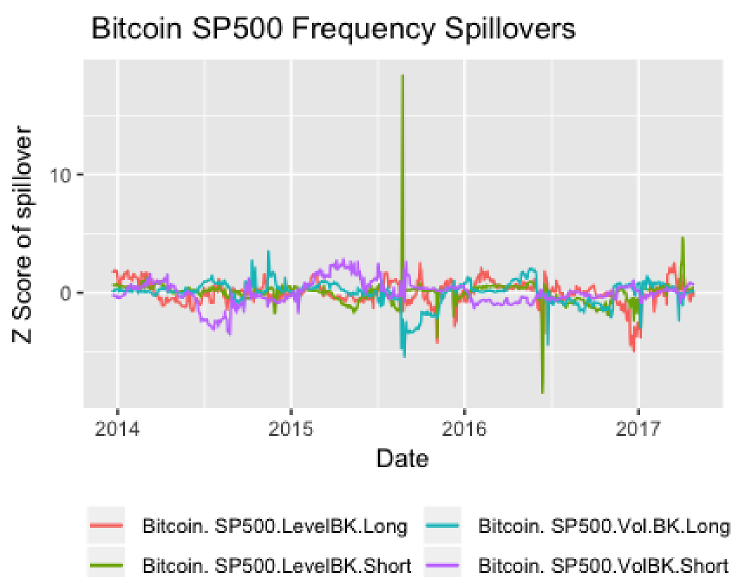

Figure 8: Bitcoin to Vix

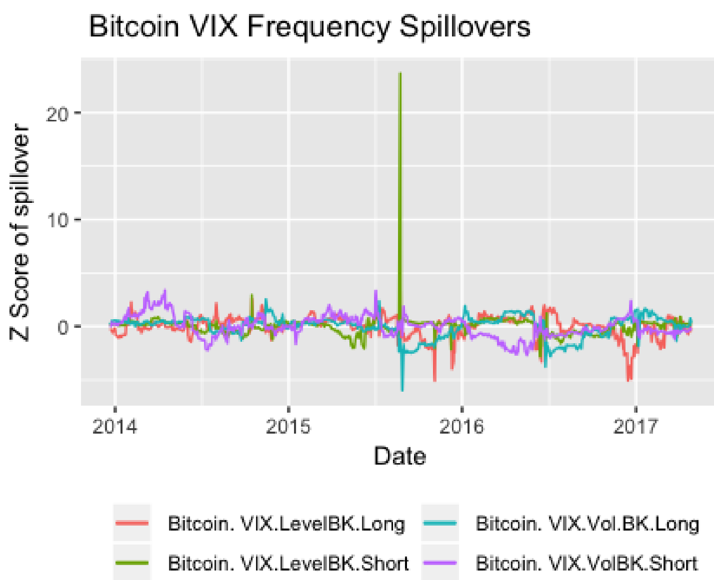

Figure 9: Bitcoin to FX

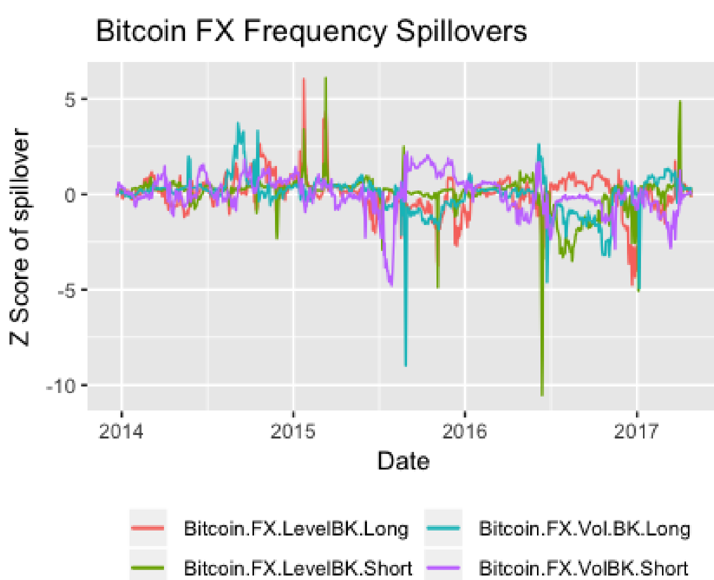

Figure 10: Bitcoin to Gold

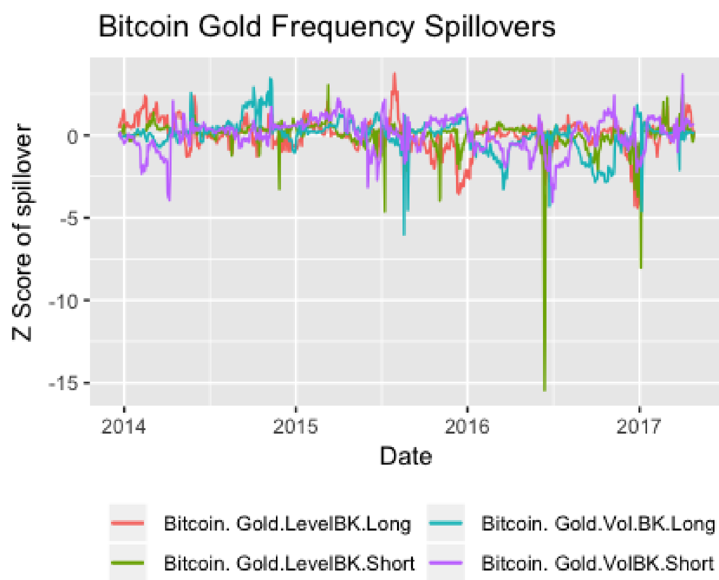

Figure 11: Bitcoin to GSCI

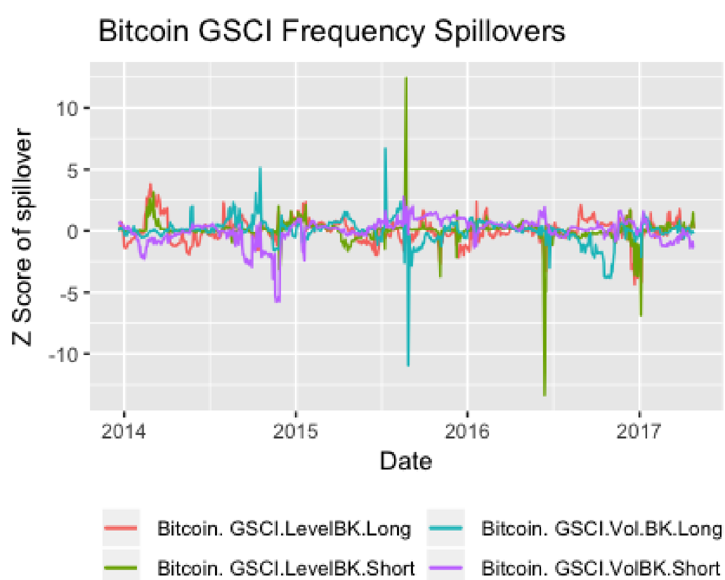

Figure 12: DCC correlations